Hybrid artificial neural networks for component design of space telemetry processing systems

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***Abstract*—This paper describes a software system of neural network control of space telemetry data for malfunction diagnosis of spacecraft subsystems. This system is used for testing of intelligent technologies for processing information about a spacecraft subsystems state, prediction and detection of irregularities of the spacecraft subsystem modes. The information obtained from on-board data sources on space communication channel is used for processing.**

***Keywords*—neural network, telemetry, spacecraft, diagnosis.**

I. Introduction

To facilitate the development of intelligent systems (ISs), it is important to ensure the reusability of ISs components. A number of design support software is known, such as SSADM, Meris, TDD, Gherkin [1]–[3]. It allows to create component-oriented, service-oriented data processing systems. Their main drawback is the lack of flexibility of the designed tools in the sense of their dynamic reconfiguration in the face of changing requirements during the software life cycle [4], [5]. The solution of this problem lies in the use of components that have the property of adapting to changing operating conditions. Their development is provided by technologies based on the ontological approach to design, on the representation of the design process by semantic networks, in particular, open semantic technologies [6]–[9]. The presence of knowledge integration tools in these development technologies reduces the process of developing a new, more advanced IS to teaching the existing one.

It is shown that neural networks (NN), which are one of the most powerful and dynamically developing tools for intelligent information processing, can be effectively used as components of applied systems. Through training, NNs allow take into account the characteristics of specific data processing components. There are a number of examples of using NNs in onboard intelligent decision support systems for controlling a complex dynamic object and diagnosing its state [10]–[14]. Their main advantage is provided by their machine learning and self-learning ability, as well as by their high degree of parallelization of processing [15].

This paper solves the problem of applying a NN approach to construct systems for operational monitoring and assessing the state of spacecraft (SC) for remote sensing of the Earth (ERS) during their operation on Earth's orbit. The input data for processing are telemetry (TM) ones, which include measurements of physical quantities characterizing the position of the SC, environmental parameters, the state of the SC equipment, subsystems and processes, transmission of the results of these measurements, registration and processing of the received TM data in flight control centers.

The complexity of the TM analysis consists in the processing quantities that are heterogeneous in physical nature and dynamic characteristics and introduce a certain uncertainty in decision-making. Thus, new monitoring methods are needed that can detect anomalies in TM data. The increased complexity of on-board systems, processing and analysis of TM data in a continuous process accompanied by noise in the information flow by non-deterministic sources of interference leads to the fact that the existing deterministic control algorithms do not provide reliable identification of abnormal modes due to partial loss of diagnostic information. The NN acts here as an apparatus for formalizing complex algorithms for information transformation. An increase in the accuracy of the analysis can be obtained by taking into account features of analyzed objects and subsystems in the NN structure. The best way to do this is to develop of hybrid (combined) NN architectures or to build ensembles of NNs (ENN).

Considering the above, some tasks are relevant. Firstly, it is necessary to develop NN models that increase the accuracy of identification and prediction of the states of subsystems of spacecraft. Secondly, it is necessary to develop a technique for TM analysis using models based on ENNs trained for individual modes of operation of SC subsystems, which ensures processing of the entire set of TM parameters of the SC, with the possibility of additional training in case of work in a non-stationary environment. The software implementation of the technique will reduce the cost of monitoring the state and behavior of the SC subsystems, since this ensures the effective use of software and hardware to solve the problem of increasing its survivability due to the rational planning of TM sessions.

II. TELEMETRY SYSTEMS

Space telemetry is a set of technologies that makes it possible to measure physical quantities characterizing the state of objects or processes, transfer the results of these measurements, register and process the received data. A telemetry system (TMS) is a part of the command and measurement systems of flight control centers.

The nature and volume of measurements are determined by the tasks of the spacecraft and can be single, constant, periodic, as required by the measurement program. The paper considers the TM of a small ERS spacecraft of the Canopus type. The Belarusian spacecraft (BSC) also belongs to this type [16].

Measurement data is transmitted to Earth, consumed locally, or both, depending on the situation.

A domestic space TM practices two-level measurements and cyclic polling of sensors, determined by the measurement program. Part of the data without any onboard processing is completely transferred to Earth, where it is processed. The other part is processed on site.

A target TM represents data from scientific equipment and remote sensing means. In the ERS spacecraft, these are photo and video cameras and spectrometers.

An important characteristic of any space system, especially its orbital part, is reliability and resilience to failures and abnormal situations and the possibility of recovery.

The diagnostic task is to recognize the operating modes based on TM signals from the corresponding sensors. The set of recognized modes forms a set of recognizable classes. The signals are very noisy. Not the original signals of the recording equipment are fed at the NN input, but they are processed (filtered) and used in the form of a vector. The output can be also a vector specifying the probability distribution over the modes of operation of the subsystems, or the number of the most probable mode.

III. TMS ARCHITECTURE

The main conceptual characteristic of NN TMS (fig. 1) is learning ability and adaptation to various TM conditions based on simulation.

The interaction subsystem is designed to collect TM data from sensors, video and cameras, telescopes, etc., as well as data on their state, and transmit control commands.

The sensor readings analysis subsystem analyzes the state of the sensors and transmits the analysis result to the control subsystem, the hardware diagnostics subsystem and the data preprocessing subsystem.

The hardware diagnostics subsystem analyzes the current state of the sensors taking into account the existing state space. It trains and extracts knowledge about possible states of equipment and identifies emergency situations based on data on the current state of sensors and on the state space. The diagnostic result is transmitted to the control subsystem.

The data preprocessing subsystem filters and removes data redundancy.

The data storage subsystem is designed to store TM data and descriptions of all possible states.

Intellectual data processing subsystem performs NN data processing.

The packet assembly subsystem fetches TM data from the database, forms and transmits packets to the data transmit/receive subsystem.

The current state transferring subsystem prepares data on the current state of the system and its sensors.

The data transmit/receive subsystem directly interacts with the radio channel, while transmission and reception can be carried out both through a communication channel (analogue of the TCP protocol) and in the form of datagrams (analogue of the UDP protocol).

The control subsystem is designed to collect and analyze data on the state of various subsystems, as well as to generate control signals.

I. BASIC ALGORITHMS FOR INTELLIGENT PROCESSING OF TM DATA

The intelligent processing subsystem consists of the following functional blocks:

1) NN block for identifying the state of the SC subsystems.
2) NN block for predicting the state of subsystems.
3) NN block for diagnostics of SC subsystems that is designed to monitor the performance of various SC subsystems.

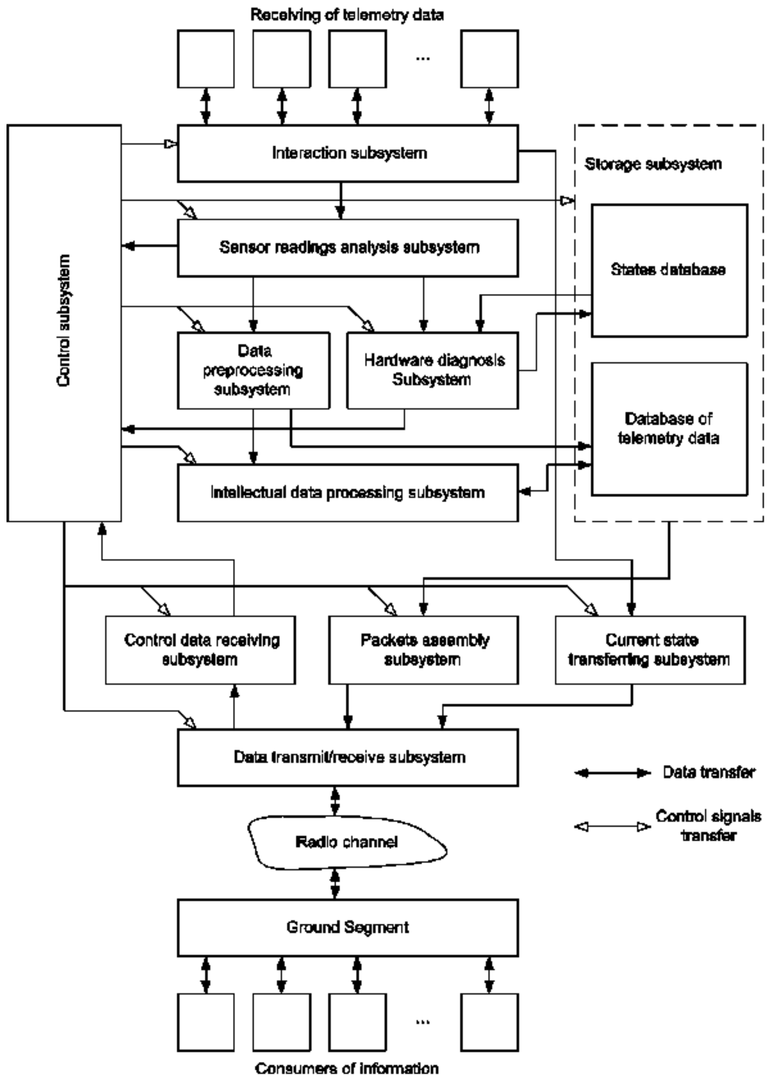

Figure 1. Block diagram of TMS

Onboard TM is a time series by its nature, including those ones with switching dynamics. A specific subsystem is characterized by a set of sensors of different types, differing in time reports (measurement frequencies), signal type, amplitudes, i.e. the time series are multidimensional. Samples of this series characterize the state of the research object at certain points in time and represent it in the space of measured features as continuous or quasi-continuous trajectories.

The type of NN depends on the types of processed signals, which are determined in turn by the specific SC subsystem and its constituent components, and the type of the problem being solved. These features are taken into account when constructing the NN model, along with taking into account the uncertainty and incompleteness of the initial information.

As a rule, the NN block consists of two parts:

- data preprocessing, which forms the input vector of NN;
- modules for constructing and training NN, recognition (calculating the output vectors of the trained NN), saving training samples in the database. Hybrid NNs are used as basic NNs.

Hybrid information processing technology involves a combination of traditional, NN and other intelligent processing methods that allow creating effective systems for processing complex structured data, when the use of only one NN method does not allow taking into account all the processing features.

Research in the field of improving the efficiency of identification and recognition based on the NN theory is carried out in the following two main areas:

1) Development of a unique, most suitable multi-layer hybrid NN model, which combines some popular NN models to effectively solve a real-life maching process. A hybrid NN model can be built from

at least two different types of NNs. The first part of the architecture is intended for preprocessing data and extracting informative features, the second is intended for making a decision in accordance with the problem being solved (segmentation, identification, classification, forecast, etc.). Various combinations of NNs are known for this purpose: multilayer perceptron, convolutional neural network (CNN), self-organizing map, long-term memory, support vector machine (SVM), recurrent NN, etc. [13], [14], [20], [21].

2) Development of ENN. These are sets of NNs that make decisions by averaging the results of individual NNs that improve the quality of identification [21]–[23]. The basic models for ENN are heterogeneous or hybrid NNs. They can be built from at least two different types of NNs.

Next, let's consider the developed base ENNs.

II. TWO-LEVEL ENN MODEL FOR PROCESSING MULTIVARIATE TELEMETRY TIME SERIES

The size N_I of the NN input layer of one ENN is determined as the product of the number of sensors in the subsystem and the time window. The size N_O of the output layer is the number of sensors in the subsystem. The size N_H of the NN hidden layer of one ENN is established when conducting an experiment with the procedure for finding the suboptimal size of the hidden layer of single NNs. Learning is carried out by the RPROP algorithm [24]. The ENN output value is generated as weighted sum of the outputs of individual NNs [25]. The weighting is repeated after specified interval of the processed time readings (dynamic weighting).

An ensemble of experts trained step-by-step on the input data (without access to the previous data) combined with a form of weighted voting for obtaining the final solution is the common of the algorithms of the drift detecting [26]–[28]. Incremental training of ENN means estimating of accuracy of all models and their ranging by accuracy at each forecasting iteration. When the error of ENN increases, the drift of the target variable is detected and a new element trained at the relevant data is added the ensemble. In this approach, we retain the model put in during the initial training and add new parameters without the problem of "forgetting". This is the way of additional training of ENN.

We solved the forecasting problem of TM data for three subsystems of the BSC. They are the power system (PS), the corrective propulsion system (CPS) and the target equipment (TE). Consequently, we generated three ENN for the TM data processing. The structure of the two-level organization of TM data processing is shown in Fig. 2.

Preprocessed TM data and the identifier of the subsystem are fed to the ENN input, which is delivered to the supervisor of the ENNs with the aid of the communication block. The supervisor generates a signal for choosing of ENN for the given subsystem and initiates the procedure of its additional training. The incremental block of additional training is responsible for preparation of the training data set and training of new elements of ENN.

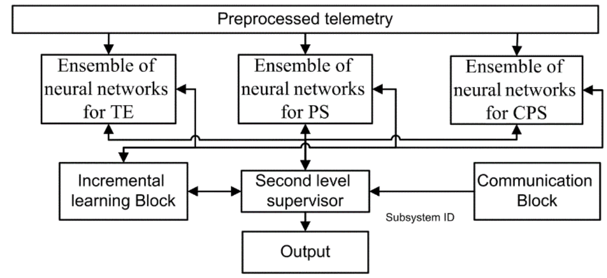

Figure 2. General scheme of telemetry data processing using ENN

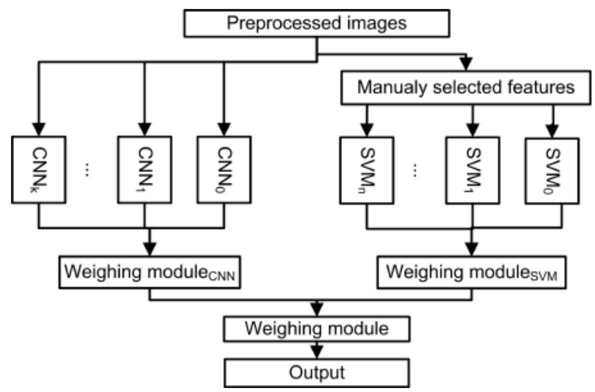

Figure 3. Ensemble of CNN and SVM models

The proposed organization of ENN in two levels implements the heterogeneity of the NN system, where the first level of the structure is represented by a set of ensembles of heterogeneous networks, and the second is represented by one generalizing module. An ensemble or a single supervisor network that processes the output values of all elements of the first level can be used as a second-level expert.

I. I. AN ENSEMBLE OF CONVOLUTIONAL NEURAL NETWORKS AND SVM MODELS

The method of support vectors is recommended to be used when working with a small set of features, so it can be chosen as the main method when forming a model from manually selected features of objects.

Thus, CNNs that receive input data directly in the form of images, and a set of SVMs that make decisions on selected features of objects can be combined into an ensemble (Fig.3).

This scheme can be modified by submitting additional features, formed without using images, directly to the input of the SVM classifiers.

CNN can be modified similarly. The network can be divided into several branches for data processing (Fig.4).

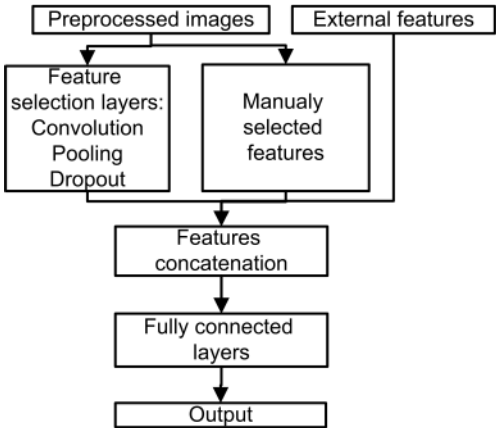

Figure 4. Hybrid CNN

One branch performs automatic feature extraction on the image using standard CNN layers, the weighting coefficients of which are determined by gradient methods during training. The other branch may include a set of predetermined preprocessing procedures, and for each input image to form an additional set of features. Also, sets of external features can be submitted to the hybrid model. This model involves two stages of training.

At the first stage, the first branch of the network is trained until sufficient accuracy is achieved, or before stopping by early stopping methods.

At the second stage, the weights of the convolutional layers of the network are fixed and the training is carried out only for fully connected layers, for which features from convolutional layers, a manual set of features, and external features come together.

CONCLUSION

A two-level model of ENNs for processing multidimensional time series of telemetry of SC subsystems is described. The experimental prototype of the software NN system was developed at the UIIP NAS of Belarus.

The proposed component design technology can be effectively supported by the OSTIS technology and basic ontology technologies for control and monitoring to describe the subject area associated with data collection using sensors and the observation (data collection) process, for example, SSN, M3, OntoSensor [29]–[32].

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Гибридные искусственные нейронные сети для компонентного проектирования систем обработки космической телеметрии

А.А. Дудкин, Е.Е. Марушко, С.А. Золотой, С. Чен

В статье описывается программная нейросетевая система контроля телеметрической информации для диагностики подсистем космических аппаратов. Предназначена для отработки интеллектуальных технологий обработки информации, поступающей по космическому каналу связи от бортовых источников данных о состоянии подсистем космических аппаратов, предсказания и обнаружения нарушений штатных режимов функционирования бортовых подсистем.

Описывается двухуровневая модель ансамблей нейронных сетей для обработки многомерных временных рядов телеметрии подсистем космических аппаратов. Входными данными для обработки являются измерения физических величин, характеризующих состояние аппаратуры, подсистем и процессов положение космического аппарата, параметры внешней среды, передачу результатов этих измерений, регистрацию и обработку полученных данных в центрах управления полетами. Предлагается также гибридная сверточная нейронная сеть, которая комбинирует признаки, выделенные нейронной сетью и экспертами. Оптимальные значения гиперпараметров моделей вычисляются методами сеточого поиска с использованием k-кратной перекрестной проверки. Представлена структура телеметрической системы. Предложена технология компонентного проектирования, которая может эффектифно поддержана технологией ОСТИС и базовыми технологиями онтологий для для описания и мониторинга предметной области, связанной со сбором данных с помощью датчиков и процессом наблюдения (сбора данных).

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